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**UNITED STATES DISTRICT COURT
NORTHERN DISTRICT OF CALIFORNIA
SAN FRANCISCO DIVISION**

**IN RE GOOGLE PLAY STORE
ANTITRUST LITIGATION**

THIS DOCUMENT RELATES TO:

*In re Google Play Consumer Antitrust
Litigation*, Case No. 3:20-cv-05761-JD

State of Utah et al. v. Google LLC et al.,
Case No. 3:21-cv-05227-JD

Case No. 3:21-md-02981-JD

**CONSUMER AND STATE PLAINTIFFS'
OPPOSITION TO DEFENDANTS'
MOTION TO EXCLUDE MERITS
OPINIONS OF DR. HAL J. SINGER**

Judge: Hon. James Donato

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Introduction

Dr. Singer’s merits expert report outlines the methodology he will use to demonstrate that Google’s conduct has harmed U.S. consumers. The market for Android App Distribution is two-sided, connecting developers who sell apps to consumers who buy them through Google Play Billing. Dr. Singer’s methodology recognizes this economic reality and models the overcharges consumers have paid through higher prices on both sides of the market. One model shows that Google’s supracompetitive take rate it charges developers has resulted in an overcharge in the form of higher app and in-app-content prices for consumers. Another shows that the lack of competition has reduced the direct consumer discounts that Google gives users, also resulting in an overcharge to the consumer side of the platform. Depending on the form competition takes in the but-for world, Dr. Singer models consumer impact and damages based on price impacts on either or both sides of the market.

Unlike at class certification, Google does not argue that any of Dr. Singer’s models—the Rochet-Tirole and Landes-Posner models used to calculate but-for take rates and consumer subsidies or the logit model used to calculate pass-through—are not generally accepted in economics. Instead, Google focuses its arguments solely on fit and on assumptions Dr. Singer made. Like at class certification, Google resorts to mischaracterizing the record and Dr. Singer’s testimony. Dr. Singer’s methods reliably demonstrate consumer impact and damages; Google’s critiques should be addressed on cross examination before a jury. Accordingly, just as this Court did at class certification, it should deny Google’s motion.

Background

Dr. Singer has again authored a comprehensive expert report and reply report disclosing the opinions he will offer at trial, including the same opinions regarding class-wide damages that were the subject of Google’s *Daubert* motion at class certification, which this Court denied. Ex. 1 (Singer Rpt.); Ex. 2 (Singer Reply); Dkt. 252; Dkt. 271; *In re Google Play Store Antitrust Litig.*, No. 20-cv-5761, 2022 WL 17252587 (N.D. Cal. Nov. 28, 2022). Google focuses solely on Dr. Singer’s analysis of antitrust impact and damages, and does not challenge his qualifications or any other opinion. Dkt. 487 (“Mot.”). For the merits, Google has retained a new expert, Dr. Gregory Leonard, whose analysis, Ex. 3 (Leonard Rpt.), repeats many of the mistakes made by Google’s class certification expert.

Google Play is a two-sided market, with app developers on one side and consumers on the other.

Understanding the need to analyze both sides of the market, Dr. Singer models how Google’s anticompetitive conduct raised prices on both sides of the market, resulting in substantial overcharges.

Overcharge from Google’s Take Rate. On one side of the market, Google extracts a supra-competitive take rate from the prices consumers pay for developers’ apps, resulting in higher prices. Ex. 1 (Singer Rpt.) ¶ 305. Dr. Singer uses two well-established models—the Rochet-Tirole Model (for the two-sided Android App Distribution Market) and the Landes-Posner Model (for the one-sided In-App Aftermarket)—to calculate the take rate Google would charge in the but-for world. *Id.* ¶¶ 305 (Table 6), 330 (Table 8). Google does not take issue with these models except to the extent pass-through is used as an input. After calculating the competitive take rate, Dr. Singer ran extensive regressions on the full available transactional data to determine the demand curves faced by developers. He then applied the resulting pass-through formula to the transactional data to calculate the portion of Google’s overcharge borne by consumers in the form of higher prices. *Id.* ¶¶ 335-63.

Overcharge from Consumer Discounts. On the other side of the market, Google currently sets a modestly negative price, by discounting consumer prices directly through a reward program called Play Points and through other discounts. *Id.* ¶¶ 371-73. In the but-for world, consumer prices would be lower because Google would offer more competitive consumer discounts to make the Play Store more attractive to consumers. *Id.* ¶¶ 374-83. Dr. Singer models this overcharge in two ways. First, he uses the same Rochet-Tirole Model, but calibrates it to solve for the but-for price on the consumer side of the market. *Id.* ¶¶ 384-388 & Table 16. This model includes a built-in incumbency advantage for Google, resulting in net discounts of [REDACTED] in the but-for world. *Id.* ¶¶ 387, 420. Dr. Singer also uses real-world consumer discounts in Amazon’s Android app store as a benchmark. *Id.* ¶¶ 417-20. Amazon provides, in the aggregate, a [REDACTED] direct discount to consumers on Google Android devices in the form of Amazon Coins. *Id.* Tables 20-21. Google claims that “Dr. Singer could not say which of these widely divergent estimates was more reliable.” Mot. at 5. Not so. Put together, Dr. Singer’s discount model and Amazon model provide a range of possible overcharges in the but-for world, with the more conservative discount model assuming a “durable incumbency advantage” in the but-for world, and the Amazon model showing Google fully matching its competitor’s discounts. Ex. 1 (Singer Rpt.) ¶ 420.

Overcharge on Both Dimensions. Google accuses Dr. Singer of offering “a smorgasbord of theories that are in tension with one another,” Mot. at 1, but that misunderstands how Dr. Singer’s models work together. In the but-for world, competitors may enter by competing on the take rate, by directly discounting prices to entice consumers to their stores, or by a mixture of both approaches. Ex. 1 (Singer Rpt.) ¶ 371. Dr. Singer provides models for each of those three forms of competition given that each of these approaches has been attempted in the actual world. Amazon has competed by offering [REDACTED] consumer discounts, focusing its competition mostly on the consumer side of the platform. *Id.* ¶¶ 417-20. Aptoide, an app store based in Europe, has offered lower take rates seeking to attract developers. *Id.* ¶ 311. The ONE Store in Korea has competed in both ways, offering lower take rates and consumer discounts. *Id.* ¶ 308. Dr. Singer models the but-for world under each of those outcomes and allows the jury to calculate damages based on its factual findings.

Use of Google Data. Google spends much of its brief deriding Dr. Singer for not directly measuring changes in app prices after Google’s limited take rate reductions. Dr. Singer did not employ the “natural experiments” Google suggests because there was not enough variation in the data. Over 90% of transactions from 2016 to 2021 took place at the 30% take rate. Ex. 4 (Hot Tub Tr.) at 60:1-4; Ex. 5 (Singer Class Reply) Fig. 1. And although Google has lowered its take rate for some transactions, Google’s anticompetitive restrictions remain in place, dampening developers’ ability and incentives to lower prices. For these reasons, the data lacks “the necessary basis for synthetic control analysis: a clean control group ... from which the Challenged Conduct is absent.” Ex. 2 (Singer Reply) ¶ 39. Because Google’s challenged conduct has been in place for the entire existence of the market, “there is no pre-existing or post-conduct time period to use for purposes of standard regression analysis.” Ex. 1 (Singer Rpt.) ¶ 280. Dr. Singer reasonably rejected the approach Google suggested he should have taken.

Moreover, Google’s criticism ignores that Dr. Singer made extensive use of Google’s transactional data, both to determine the demand curve faced by developers and to directly measure pass-through of *ad valorem* (i.e., percentage) costs. To determine the demand curve faced by developers, he ran regressions across every single transaction in the database across the entire damages period, ranging from August 16, 2016 to May 31, 2022. Ex. 1 (Singer Rpt.) ¶ 353. Dr. Singer also used corroborative empirical evidence of pass-through by showing that higher tax rates—which like Google’s take rate, are

an *ad valorem* cost—“are systematically passed on by developers to consumers in the form of higher prices” across Google’s voluminous transactional data. Ex. 2 (Singer Reply) ¶ 8.

Dr. Leonard’s Flawed Experiments. Google claims Dr. Leonard’s “multiple analyses of six different data sets of IAPs at the SKU level, covering hundreds of products” shows [REDACTED] in the real world, Mot. at 4, but ignores the significant flaws with those experiments. Dr. Leonard conducted two types of analyses—a simple before and after price comparison for six overlapping sets of 100 SKUs, and a “synthetic control” regression—on prices after Google reduced the take rate to 15% on the first \$1 million in each developer’s revenue in mid-2021. Ex. 3 (Leonard Rpt.) ¶¶ 36-54. While Dr. Singer used almost six years of available data, Dr. Leonard analyzed less than a year’s worth of data after the take rate declined (July 2021 to May 2022). Ex. 2 (Singer Reply) ¶ 22; Ex. 3 (Leonard Rpt.) ¶¶ 36-54.

Both of Dr. Leonard’s analyses relied on the same flawed SKU-level methodology of Google’s class certification expert. Ex. 2 (Singer Reply) ¶ 5; Ex. 5 (Singer Class Reply) ¶¶ 123-133. That methodology’s sole focus on individual SKUs is wholly unreliable because it misses the forest for the trees, ignoring the actual products developers sell and the multiple ways developers can change prices. *Id.*¹ Dr. Leonard’s analyses of a narrow time period and transient reductions in take rate further compound these issues, make his conclusions especially susceptible to price stickiness concerns, and do not allow time for developers to internalize Google’s [REDACTED] take rate reductions. Ex. 2 (Singer Reply) ¶ 23. And as described below, both of his analyses also suffer from significant additional flaws.

First, Dr. Leonard analyzed “six different data sets,” Mot. at 4, that each contained only 100 SKUs. Ex. 3 (Leonard Rpt.) ¶¶ 36-43. These six sets of 100 SKUs—3 sets of in-app purchases and 3 sets of initial app purchases—overlap significantly, meaning that Dr. Leonard analyzed fewer than 600 SKUs (not products) in total. *See* Ex. 6 (Leonard Dep.) at 37:4-19. Dr. Leonard did not know how many SKUs were in the full data set and acknowledged that some apps individually contain hundreds of SKUs for in-app purchases. *Id.* at 39:13-15, 41:15-18. In total, the SKUs Dr. Leonard analyzed represented “[REDACTED] of aggregate purchases” by Consumers over the period he studied. Ex. 2

¹ Dr. Leonard claims to have ruled out some of these issues, Ex. 3 (Leonard Rpt.) ¶ 43 n.30, but he failed to take basic steps to analyze how developers use SKUs. For the SKUs he analyzed, he did not determine whether other SKUs in the same app changed their price, and he did not even know what products the SKUs he analyzed represented. Ex. 6 (Leonard Dep.) at 47:11-16, 48:9-49:24.

(Singer Reply) ¶ 21. Because the take-rate reduction Dr. Leonard analyzed applies only to the first million in developer revenue, many of the SKUs he analyzed experienced only fleeting take rate reductions, sometimes [REDACTED]. Ex. 3 (Leonard Rpt.) ¶ 41 & Fig. 3. Moreover, Dr. Leonard admitted that he does not know whether the SKUs he analyzed are “[REDACTED]” and performed no analysis to determine if they were. Ex. 6 (Leonard Dep.) at 59:19-61:4.² Nor did Dr. Leonard control for whether any factors aside from the service fee reduction affected the price of the SKUs he analyzed. *Id.* at 47:17-48:2. Dr. Leonard also failed to adjust for inflation, even though the time period featured significant inflation. Ex. 2 (Singer Reply) Figs. 1-3.³

Second, Dr. Leonard ran a “synthetic control” regression, comparing developers whose take rate remained the same (control group) to those who received a reduction in July 2021 (treatment group). Ex. 3 (Leonard Rpt.) ¶¶ 47-54. His treatment group included only *one percent* of transactions over that already limited period. Ex. 2 (Singer Reply) ¶¶ 35, 38. The treatment group contained developers making significantly less revenue (averaging [REDACTED] per year) than those in his control group (averaging [REDACTED] million per year). *Id.* ¶ 37. Due to these and other issues, Dr. Leonard’s analysis produced nonsensical results. His analysis was unable to determine the sign, let alone the magnitude, of the pass-through rate, so he arbitrarily used the extreme upper bound of the 95% confidence interval from his regression analysis to calculate his 3% pass-through rate. *Id.* ¶ 39; Ex. 3 (Leonard Rpt.) ¶ 51.

Argument

I. Dr. Singer’s Pass-Through Analysis Is Reliable

Dr. Singer’s pass-through analysis, which is grounded in extensive empirical work, is reliable. Google now appears to concede that the “logit model is sometimes used for other kinds of antitrust analyses.” Mot. at 6. As such, Google does not argue that Dr. Singer’s method is not “generally accepted,” which is a “key factor” in the *Daubert* analysis. *See Milan v. Clif Bar & Co.*, 340 F.R.D. 591,

² Dr. Leonard declined to analyze any subscription SKUs except for Tinder in his “real-world analysis” because [REDACTED].” Ex. 6 (Leonard Dep.) at 61:21-62:14.

³ Dr. Leonard claims to rule out inflation because he found “no statistically significant relationship” between inflation and Android app prices. Ex. 3 (Leonard Rpt.) ¶ 38 n.14. But Dr. Leonard’s finding of no relationship is equally consistent with [REDACTED], just as Dr. Singer’s analysis showed. Ex. 7 (Singer Merits Dep.) 133:12-18.

601 (N.D. Cal. 2021); *see also* Ex. 1 (Singer Rpt.) ¶ 348 n.809. Google instead focuses its arguments on fit, arguing that “Plaintiffs have the burden to show that Dr. Singer’s formula in *this case* is reliable.” Mot. at 6. As an initial matter, Dr. Singer’s application of logit is directly analogous to the merger context—the objective is to map a change in costs onto a change in price. *See* Ex. 4 (Hot Tub Tr.) at 61:18-20. More specifically, none of the factors Google identifies undermine the fit of Dr. Singer’s methods to this case, or the logit model’s fit to Google’s transactional data.

A. Logit Reliably Models Demand for Each of Google’s App Categories.

Google argues that “[i]f logit does not reliably model user demand, then Dr. Singer’s formula derived from logit is not reliable.” Mot. at 6. Neither Google nor its experts argue that another demand curve fits the facts of this case better.⁴ Instead, Google focuses solely on whether the logit demand system’s property of proportional substitution (also known as “independence of irrelevant alternatives” or “IIA”) is satisfied. Proportional substitution means that when prices for one product increase, consumers switch to substitutes in proportion to their relative shares. The facts support the use of proportional substitution, and logit models can reliably measure pass-through even if proportional substitution does not perfectly hold.

First, Dr. Singer has demonstrated that logit does reliably model user demand, and Google does not present any reliable evidence showing otherwise. Dr. Singer’s regressions show that logit “explain[s] over 95 percent of the variation in consumer demand in the voluminous Google transaction data.” Ex. 2 (Singer Reply) ¶ 7. For each of the Play Store’s categories, Dr. Singer finds a [REDACTED] relationship between price and share within that category. Ex. 1 (Singer Rpt.) ¶ 354. Dr. Singer has also tested logit against alternative models. Ex. 2 (Singer Reply) ¶ 51 & Appendix 3; Ex. 7 (Singer Merits Dep.) 114:18-116:5. Dr. Singer’s use of standard econometric methods to confirm logit’s fit is “standard practice in empirical antitrust work,” wherein “the form of the demand curve is

⁴ Google’s only passing effort to suggest another demand model would work is by noting that Dr. McFadden used log-linear demand rather than logit demand in the Apple litigation. Mot. at 8 n.3. But the fact that Dr. McFadden used a different model—while using the same app categories to calibrate his model—is of no matter. Dr. McFadden concedes that his log-linear equations are meant only to “approximate consumer demand” (in the market for iOS apps, not Android apps) and there is no indication that Dr. McFadden tested (let alone rejected) logit demand. *In re Apple iPhone Antitrust Litig.*, No. 4:11-cv-6714-YGR (N.D. Cal.), Dkt. 643-11 at 151, Appendix D, ¶ 7.

assessed based on ‘how well the model fits the observable data.’” Ex. 2 (Singer Reply) ¶ 7 (quoting Ex. 8 (Luke Froeb et al., *Economics at the Antitrust Division: 2017–2018*, 53 REVIEW OF INDUSTRIAL ORGANIZATION 637, 640 (2018))).

“[T]he logit model makes a very specific prediction about the relationship between an app’s share within its category and its price,” and Dr. Singer’s regressions confirmed that relationship. Ex. 4 (Hot Tub Tr.) at 81:21-82:22. As Dr. Singer testified, “once you know that the model fits and is the best demand system for the data, you can infer that users are moving around the category in proportion to the market share.” Ex. 7 (Singer Merits Dep.) 188:10-15. Google seeks to cast doubt on Dr. Singer’s empirical analysis—even though it has not moved to exclude it—by truncating Dr. Singer’s deposition testimony to suggest his methods are unsupported. Mot. at 9 (quoting excerpts of Singer Merits Dep.). The full answer Google omits shows that “goodness of fit will tell you if the Logit is ... the relevant way to describe preferences in substitution patterns here.” Ex. 7 (Singer Merits Dep.) at 104:12-105:6, 105:23-106:8.⁵

In contrast to Dr. Singer’s data analysis, which confirms that logit describes demand within each app category well, Google relies solely on anecdotal argument. Dr. Leonard has not performed any empirical analysis of substitution. Ex. 3 (Leonard Rpt.) ¶ 66. Nor has Google identified any alternative analysis Dr. Singer could have performed.⁶ Lacking empirical support, Google argues that “just one” example will do, highlighting QuickBooks Online Accounting, an accounting app, and Thumbtack, an app that connects consumers to professionals. Mot. at 9. But even Google’s one example fails because

⁵ Dr. Rysman’s testimony which Google cites, Mot. at 9 n.4, simply says that “negative correlation between price and demand” would “[n]ot by itself” indicate that “the logit model was appropriate.” Ex. 9 (Rysman Dep.) 68:21-69:2. Dr. Rysman had not read Dr. Singer’s report. *Id.* at 42:21-25.

⁶ No expert in this case has applied the statistical test for logit developed by Hausman and McFadden, given that it is not applicable here. Ex. 7 (Singer Merits Dep.) 86:17-87:6, 96:12-20, 103:19-104:11. Logit is commonly used without applying that test. *See, e.g.*, Ex. 10 (Frank Verboven & Theon van Dijk, *Cartel Damages Claims and the Passing-on Defense*, 57(3) JOURNAL OF INDUSTRIAL ECONOMICS 457, 457-91 (2009)) (Hausman-McFadden test not mentioned in article using logit to measure pass-through from cartel); Ex. 8 (Froeb 2018) (Hausman-McFadden test not mentioned in discussion of DOJ economists’ use of logit, nor offered in the accompanying antitrust software manual, available at: <https://cran.r-project.org/web/packages/antitrust/antitrust.pdf>); Ex. 11 (Frank Verboven, *International Price Discrimination in the European Car Market*, 27(2) RAND JOURNAL OF ECONOMICS 240, 240-68 (1996)) (Hausman-McFadden test not mentioned in logit analysis of European auto pricing).

QuickBooks and Thumbtack are substitutes. Thumbtack includes professional listings for “Accountant,” “Small Business Accounting,” and “Business Accounting,” which a user could employ rather than buying QuickBooks. Ex. 12 (Thumbtack Webpage Excerpts).

Substantial record evidence likewise supports that Google’s app categories meaningfully organize substitution. Google dismissively says that its “maintenance of the categories says nothing about substitution between apps,” Mot. at 9, but ignores that it does more than just maintain the categories. Evidence shows that the Play Store’s categories are not “haphazardly assigned or done without any kind of economic logic.” Ex. 7 (Singer Merits Dep.) 90:11-12. Google tells developers that “[c]ategories and tags help users to search for and discover the most relevant Apps,” Ex. 1 (Singer Rpt.) ¶ 349 (citation omitted), and uses the categories [REDACTED]. *E.g.*, Ex. 13 (GOOG-PLAY-000579868.R) at -870.R; Ex. 1 (Singer Rpt.) ¶¶ 349-51 (compiling Google and external analyses that [REDACTED]). The categories represent economically reasonable groupings of consumer tastes for different varieties of Apps. Ex. 1 (Singer Rpt.) ¶ 349.

Second, even accepting Google’s inaccurate factual contentions, Google’s premise that logit fails if even one app in a category is not a substitute is false. Logit “does not imply that all products in the market are perfectly interchangeable, but instead allows for product differentiation.” Ex. 1 (Singer Rpt.) ¶ 351 (citing peer-reviewed literature). As Dr. Singer testified, even if proportional substitution does not hold for *every* app, the logit model would still be reliable, because “[i]n any econometric model ... we make all sorts of demands on the nature of the error terms in the model, just as we do here.” Ex. 7 (Singer Merits Dep.) 89:20-90:16. Even if proportional substitution is not strictly satisfied, an economist may “use the logit model ... considering the model to be an approximation.” Mot. Ex. 8 (Train, *Logit*) at 36.

For this reason, Google’s excerpts of testimony suggesting Dr. Singer concedes that not all apps in a given category are perfect substitutes get it nowhere. In each case, Dr. Singer noted that even if each app is not a perfect substitute, the model provides a reasonable estimation of competition within the category. *See* Ex. 14 (Singer Class Dep.) at 158:6-160:1; Ex. 4 (Hot Tub Tr.) at 116:13-117:21 (categories “are a meaningful arena of competition around which one can use for estimating shares for the logit model”).

Neither Google’s brief nor its economist cite any literature for the proposition that cherry-picked

examples of apps that are not perfect substitutes within a category undermine pass-through estimates. Ex. 3 (Leonard Rpt.) ¶ 72 n.76; *see also id.* ¶ 153 (arguing only that “IIA restrictions on substitution patterns can be especially misleading in the context of new product introduction”). As Dr. Singer has explained, logit does not require that all apps within a category are substitutes from the perspective of all consumers. Ex. 7 (Singer Merits Dep.) 78:17-21. Meanwhile, Dr. Singer has cited extensive literature showing that logit is widely used to estimate pass-through in a variety of contexts.⁷

Google’s citations concerning unrealistic “forecasts” from the logit model concern an entirely different application of logit. Each concerns the reliability of forecasting consumer substitution when new or different products are introduced. *See* Mot. Ex. 9 (McFadden, *Economic Choices*) at 357-58 (logit gives “an easy formula for forecasting demand for new alternatives”); Mot. Ex. 8 at 47-48 (discussing non-proportional substitution from small and large gas cars to small electric cars). As Dr. Singer explained: “the forecast that McFadden [the author of Mot. Ex. 9] has in mind here are forecasts that are made from the parameters of the Logit model after it’s estimated, right. I’m not making any such forecast. That’s not what I’m using it for.” Ex. 7 (Singer Merits Dep.) 418:17-419:20. Put differently, Dr. Singer’s pass-through model does not rely on forecasting consumer substitution to new or different products; consumers make the *same purchases* at lower prices after take rates fall across the board.

B. Dr. Singer Accounted for Focal Point Pricing

Google’s argument that Dr. Singer fails to consider focal point pricing fails for two basic reasons. Google has not shown that focal point pricing will affect pricing in the but-for world, and Google ignores that Dr. Singer’s methodology can account for focal point pricing.

First, there is very little evidence that focal point pricing would dictate pricing in the but-for world. Dr. Singer presented significant evidence that developers can and do depart from 99-cent focal point intervals. Ex. 1 (Singer Rpt.) ¶ 405. For example, Google previously mandated a 99-cent price

⁷ *See, e.g.*, Ex. 1 (Singer Rpt.) ¶ 356, nn.835-37; Ex. 15 (Nathan Miller, et al., *Pass-Through and the Prediction of Merger Price Effects*, 64(4) JOURNAL OF INDUSTRIAL ECONOMICS 683, 693 (2016)) (Table 1 shows pass-through estimates for logit); Ex. 10 (Verboven & van Dijk 2009) (using logit to analyze the extent to which direct purchasers overcharged by the European vitamin cartel would pass on the overcharges to indirect purchasers.); Ex. 16 (K. Sudhir, *Structural Analysis of Manufacturer Pricing in the Presence of a Strategic Retailer*, 20(3) MARKETING SCIENCE 244, 249-51 (2001)) (using logit to analyze pass-through of wholesale supermarket prices into retail prices paid by consumers).

1 floor; approximately [REDACTED] of developers reduced their prices below 99-cents within the first year that
 2 restriction was lifted. Ex. 1 (Singer Rpt.) ¶ 406; Ex. 7 (Singer Merits Dep.) at 121:16-122:2. Google’s
 3 evidence of the importance of 99-cent focal point intervals is limited to one footnote in Dr. Leonard’s
 4 report, Ex. 3 (Leonard Rpt.) ¶ 32 n.7, even as Dr. Leonard elsewhere argues that “there are *many* different
 5 price points across apps” and that “there are rarely two apps that have the same price,” *id.* ¶ 142 & Figs.
 6 14-17. Dr. Singer thus reasonably concluded that “the prospect of focal point pricing getting in the way,
 7 even for those [developers] who care about it ... of a price reduction is ... remote.” Ex. 7 (Singer Merits
 8 Dep.) 122:3-123:3.⁸ Here there is no “overwhelming evidence” suggesting that “developers would
 9 choose to price their apps at focal points ending in 99 cents.” *In re Apple iPhone Antitrust Litig.*, No. 11-
 10 cv-6714-YGR, 2022 WL 1284104, at *8 (N.D. Cal. Mar. 29, 2022). There is little reason for Dr. Singer
 11 to account for focal point pricing in his models on this record.

12 *Second*, even if focal point pricing would guide but-for world pricing, Dr. Singer has empirically
 13 demonstrated that his model can accommodate it. Ex. 1 (Singer Rpt.) ¶¶ 407-13. In short, Dr. Singer’s
 14 model can be modified such that the developer reduces the price to the nearest focal point interval, rather
 15 than precisely to the but-for profit-maximizing price. *Id.* ¶¶ 411-12. Using 10-cent focal point intervals,
 16 which Dr. Singer notes are common in Google’s transactional data, adjusting for focal point pricing
 17 resulted in only [REDACTED] of transactions not seeing a price decrease in the but-for world. *Id.* ¶¶ 407, 413.
 18 Dr. Singer demonstrated that his model can be mechanically adjusted to account for focal point pricing.

19 **C. Dr. Singer Accounted for Developers’ Costs**

20 Dr. Singer’s pass-through calculations account for developers’ other marginal costs beyond the
 21 take rate. The initial equations from which the standard logit pass-through formula was derived include
 22 a term for developers’ marginal costs. *See* Ex. 17 (Nathan Miller, et al., *Using Cost Pass-through to*
 23

24
 25 ⁸ Google selectively quotes Dr. Singer’s testimony and outright mischaracterizes Dr. Rysman’s
 26 testimony on focal point pricing. Google’s claim that Dr. Singer concluded that “focal point pricing is
 27 an important consideration here” takes that exchange out of context, and any implication that Dr. Singer
 28 did not consider it is belied by his report and other deposition testimony. *See* Ex. 7 (Singer Merits Dep.)
 at 121:8-15; Ex. 1 (Singer Rpt.) ¶¶ 405-06; Ex. 2 (Singer Reply) ¶ 8 n.21. Google claims Dr. Rysman
 conceded that “some firms would not change price in response to a change in the commission rate.” Mot.
 at 2 (quoting Rysman Dep.). Dr. Rysman said that would be the case “[i]f focal point pricing is
 important,” but then testified “I didn’t study that issue.” Ex. 9 (Rysman Dep.) at 62:16-63:15.

1 *Calibrate Demand*, 118 ECONOMICS LETTERS 451, 452-453 (2013)). As Dr. Singer testified, when “you
2 look at the most common functional forms [of demand curves,] [y]ou’ll often see that marginal cost
3 drops out of the pass-through equation.” Ex. 7 (Singer Merits Dep.) 147:9-17. In short, standard
4 economics shows that knowledge of developers’ *other* marginal costs is not necessary to calculate pass-
5 through.

6 Google cites only Dr. Leonard’s report and selections of Dr. Singer’s deposition to say he should
7 have done more to account for those costs. But Dr. Leonard cites no literature in support of his claim,
8 Ex. 3 (Leonard Rpt.) ¶ 32 & n.7; Ex. 6 (Leonard Dep.) at 104:23-105:6, and relies solely on his own
9 calculations that do not appear in any literature, Ex. 6 (Leonard Dep.) at 106:5-110:3. Google also repeats
10 its false claim from class certification that “Dr. Singer concedes that pass-through of a service fee will
11 be proportional to the developer’s other marginal costs.” Mot. at 2; Dkt. 252 at 7. That testimony
12 concerns a separate equation which cannot be used—and that no expert has suggested could be used—
13 to calculate pass-through. Ex. 14 (Singer Class Dep.) at 105:8-109:14. Google’s citation omits the middle
14 of the quoted exchange, where Dr. Singer specifies that “when I go to model the precise amount of pass-
15 through,” it “takes me to a pass-through rule that isn’t necessarily going to be denominated in terms of
16 costs.” *Id.* at 107:8-22. As noted above, other marginal costs drop out of the equation once a demand
17 curve is applied. Ex. 17 (Miller 2013) at 452-53. Google has no support for its suggestion that Dr. Singer
18 needs to determine every developer’s exact level of other marginal costs to determine pass-through.⁹

19 **D. Dr. Singer Used Extensive Available Data**

20 Finally, Google argues that Dr. Singer has not “conducted any statistical analysis” of pass-
21 through and instead “has chosen a formula to guarantee it.” Mot. at 11-12. Again, Google is wrong—
22 Dr. Singer used data at every step of his analysis. Dr. Singer did not simply “choose” the logit formula—
23 he ran regressions across Google’s transactional data to confirm that logit described the demand faced
24 by app developers better than other demand curves. Ex. 2 (Singer Reply) ¶ 7 & n.19. This case is nothing
25 like *Sidibe v. Sutter Health*, 333 F.R.D. 463 (N.D. Cal. 2019), where the expert simply assumed 100%
26 pass-through based on one document in the record. *Id.* at 497. Dr. Singer also used Google’s transaction
27

28 ⁹ Indeed, doing so would be impossible—Dr. Leonard testified with respect to each developer’s
marginal costs: “[REDACTED].” Ex. 6 (Leonard Dep.) at 87:13-88:7.

data to confirm that developers pass through *ad valorem* taxes (similar to the take rate here) in the form of higher prices. Ex. 2 (Singer Reply) ¶ 8. Finally, Dr. Singer engaged with, and extensively rebutted, Dr. Leonard’s use of Google’s transaction data. *Id.* ¶¶ 19-39.

In fact, Dr. Leonard has employed similar methods to Dr. Singer’s work in the past. Dr. Leonard represented the merging companies in FTC proceedings related to the merger of Staples and Office Depot. Ex. 18 (Jerry Hausman & Gregory Leonard, *Efficiencies from the Consumer Viewpoint*, 7(3) GEO. MASON L. REV. 707, 726 (1999) (PX-2853)). There, the FTC conducted an empirical study and found that only 21% of cost savings from the merger would be passed on to consumers. *Id.* Dr. Leonard criticized this empirical estimate as “implausibl[e]” suggesting the FTC’s “estimates were downward biased, e.g., because of measurement error.” *Id.* at 726 n.47. Dr. Leonard found that the “[demand] curvature implied by the Staff’s pass-through estimate” was “quite unlikely to hold in practice.” *Id.* at 726. Dr. Leonard concluded that “[t]he knowledge that at least 50 percent of the cost savings will be passed on to consumers could have a significant effect on the Agencies’ evaluations of merger[s].” *Id.* at 727. Put simply, Dr. Leonard concluded that an analysis like Dr. Singer’s—using the demand curve to derive a pass-through rate—was more reliable than an empirical analysis of a subset of data—as Dr. Leonard did here.

At bottom, Google’s argument is not that Dr. Singer ignored available data, it is that his use of the data and analysis draws conclusions Google doesn’t like. Disagreement with the *output* of an expert’s methodology is no grounds for exclusion. *Elosu v. Middlefork Ranch Inc.*, 26 F.4th 1017, 1024 (9th Cir. 2022) (“Ultimately, the test under *Daubert* is not the correctness of the expert’s conclusions but the soundness of his methodology.” (quotation marks and citation omitted)).

II. Dr. Singer’s Consumer Subsidy Overcharge Models Are Admissible and Reliable

Google argues that Dr. Singer’s consumer subsidy models are both inadmissible for the class and unreliable. Neither argument has merit. As a preliminary matter, that the Court did not rely on the model at class certification is of no matter. *Comcast Corp. v. Behren* stands for the proposition that damages must be connected to “the particular antitrust injury on which [defendant’s] liability in this action is premised.” 569 U.S. 27, 36 (2013). Unlike in *Comcast*, each of Dr. Singer’s damages models flow from the same theory of antitrust impact—that Google’s conduct has blocked competitors from the Android

App Distribution Market and In-App Aftermarket resulting in higher consumer prices—but models that price impact on separate ends of the market. *See Krueger v. Wyeth, Inc.*, 310 F.R.D. 468, 482 (S.D. Cal. 2015) (“[u]nlike the situation in *Comcast*, there is no possibility in this case that damages could be attributed to defendants’ acts that are **not** challenged on a class-wide basis”). There is no *Comcast* issue because both models flow from the same theory of liability. And, of course, Dr. Singer may present his other models on behalf of the States and individual consumers.¹⁰

Dr. Singer’s calculations of overcharge damages based on discounts are also reliable. The discount model is built upon the same Rochet-Tirole model that Google does not challenge, with the exception of some inputs. The Amazon model is built on a reliable benchmark of the real-world entrant that has chosen to compete with consumer discounts.

A. Dr. Singer’s Discount Model Is Reliable

Google raises two issues with Dr. Singer’s discount model: (1) that he failed to analyze Play Points participation rates with specificity, and (2) that he used unreliable economic data for one input. Both criticisms are at best grist for cross-examination and do not merit exclusion of his testimony at trial.

First, Dr. Singer relied on substantial record evidence to conclude that the discounts Google provides consumers in the but-for world would benefit all or nearly all consumers. About [REDACTED] of consumers have already signed up for Play Points today, even though the Play Points subsidy “is [REDACTED] right now.” Ex. 14 (Singer Class Dep.) 293:21-294:9; 298:4-21. In a more competitive world, Google would have clear economic incentives to automatically provide discounts to users, or at least to minimize enrollment costs, so “they would not be so prohibitive as to allow [a but-for] rival to eat their lunch.” Ex. 7 (Singer Merits Dep.) 168:19-169:7. Substantial record evidence shows that even modestly higher discounts lead to widespread enrollment. Ex. 1 (Singer Rpt.) ¶¶ 371-383; Ex. 19 (AMZ-GP_00002484) at -488 (greater than [REDACTED] usage of Amazon coins); Ex. 20 (GOOG-PLAY-000004957.R) at -969.R (“[REDACTED]” for Play Points [REDACTED] within just one year).

¹⁰ Google also claims Dr. Singer opined that the model only addresses “aggregate damages,” but as Dr. Singer explained shortly after: “for a given member of the class, you could estimate what the reduction in – in his or her net payments would be relative to what they spent in the actual world.” Ex. 7 (Singer Merits Dep.) at 164:17-166:14; *see also id.* at 172:7-12 (“Q: And if I – again, if I took a user at random from the – from the data on the users of the Google Play Store, could your Amazon Coins model tell me whether – how much in subsidy that consumer would have received? A: Yes.”).

Dr. Singer relied on that evidence to conclude that “a safe inference is that all or almost all consumers will avail themselves of that option.” Ex. 7 (Singer Merits Dep.) 167:11-25. Google has not shown why he must do more to account for low participation rates that flow from current meager discounts, an artifact of Google’s conduct. *See In re Mushroom Direct Purchaser Antitrust Litig.*, No. 06-0620, 2015 WL 5767415, at *6 (E.D. Pa. July 29, 2015) (reliable method “may properly include making assumptions so long as those assumptions are sufficiently grounded in available facts” (citation omitted)).

Second, Google criticizes one of the inputs to the discount model. Dr. Singer made a reasonable economic choice in relying on peer-reviewed literature studying AT&T as its market share declined to 60% with competition to calculate the but-for price elasticity. Ex. 1 (Singer Rpt.) ¶ 386 n.920. Economic models are not industry-specific; what matters are similarities in competitive dynamics—AT&T is a prime example of a platform monopolist, benefitting from network effects, that leveraged monopoly power into an ancillary market, before being forced to open the market to competition. *See id.* ¶ 331; Ex. 2 (Singer Reply) ¶ 42. If Google’s criticism is that a higher tech benchmark is necessary, Dr. Singer also provided several other benchmarks which result in a *lower* but for market share—and *higher* damages—demonstrating that his use of AT&T was conservative. *Id.* ¶¶ 43-46 (analyzing post-monopolistic market shares of Netflix (25%), IBM (24.6%), and Internet Explorer/Edge (4%)). Neither Google nor Dr. Leonard have proposed an alternative benchmark or calculated an alternative but-for market share.

Finally, the precise value of Google’s but-for market share does not “dramatically” affect Dr. Singer’s model as Google suggests. Mot. at 13. Changes to this single input result in only minor changes in the model’s predictions. Ex. 7 (Singer Merits Dep.) 151:24-153:4; *see also* Ex. 2 (Singer Reply) ¶ 49. Thus, even if the AT&T benchmark is not precise, it does not significantly impact the results. In any case, criticisms of an input are grounds for cross-examination, not exclusion. *See Victorino v. FCA US LLC*, No. 16-cv-1617-GPC, 2018 WL 2767300, at *3 (S.D. Cal. June 7, 2018) (“[u]nder Rule 702 and Daubert, the proper analysis is not whether some of the inputs can be questioned” (citation omitted)).

B. Dr. Singer’s Amazon Model Is Reliable

Finally, Dr. Singer’s Amazon Model is a reliable alternative measure of overcharge to consumers, based on a benchmark of Google’s most prominent worldwide competitor that courted consumers with discounts. Google’s arguments to the contrary are merely cross examination points.

1 *First*, as with the discount model, Dr. Singer’s Amazon model can calculate individual damages.
 2 The discount derived from the model can be mechanically applied to each consumer’s purchase history,
 3 just as with the other models. *See* Ex. 7 (Singer Merits Dep.) 171:22-172:12.

4 *Second*, the discounts Amazon provides to consumers on Android devices are a reliable
 5 benchmark for Google’s consumer subsidies in a but-for world where it would have been forced to
 6 compete for consumers directly by lowering app prices. The Amazon app store is the only available
 7 benchmark (1) of a store competing in the Android App Distribution Market through use of consumer
 8 discounts; (2) of a rival with Amazon’s stature; (3) with record evidence indicating a sustained attempt
 9 at robust competition on Google Android devices; and (4) with available data revealing the magnitude
 10 of discounts actually received by consumers in the actual world. Ex. 1 (Singer Rpt.) ¶¶ 198-200, 417-20.
 11 While other app stores on Android may meet some of those points, Google has not identified any
 12 alternative benchmark that meets these (or similar) criteria. For example, while ONE Store offered
 13 consumer discounts in Korea, it does not have the same worldwide reach as Amazon, and data
 14 quantifying its discounts is not available. *Id.* ¶¶ 308, 377; Ex. 7 (Singer Merits Dep.) 181:18-182:11.¹¹
 15 This is not a situation like *In re Apple iPhone Antitrust Litig.*, 2022 WL 1284104, at *3-4, where an
 16 expert “cherry-picked” one of many benchmark candidates from a different market.

17 Google also complains that Amazon offers its discount (coins) in a different form than Google
 18 offers its discounts (points) in the actual world. But it does not explain why that makes Amazon a less
 19 effective benchmark—the key point is that Amazon was willing to (and did) fund discounts of [REDACTED]
 20 to attract consumers. The relevant economic question is the total discounts consumers would receive,
 21 and a competitor could sustain, in the face of competition. Ex. 2 (Singer Reply) ¶ 56. In a competitive
 22 market, Google would have the incentive to not only match those discounts, but to provide them in either
 23 the same form, or in a form that is just as valuable to consumers, so that it could effectively compete.

24 **Conclusion**

25 For the foregoing reasons, Google’s motion to exclude Dr. Singer’s testimony should be denied.

26
 27 ¹¹ Google claims that Dr. Singer did not “analyze whether any other app stores that his report identifies
 28 as potential benchmarks” would be a better fit. Mot. at 15. But the testimony Google cites *does* analyze
 ONE Store, and the other items in that table, with the exception of Aptoide, are not Android app stores.
 Ex. 7 (Singer Merits Dep.) 181:18-183:5 (referencing Table 7 of Ex. 1, Singer Rpt.)

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I, Karma M. Giulianelli, am the ECF User whose ID and password are being used to file this document. In compliance with Civil Local Rule 5-1(h)(3), I hereby attest that each of the signatories identified above has concurred in this filing.

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